Optimal Deep Learning based Classification Model for Mitral Valve Diagnosis System

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Abstract*: *In present days, the domain of mitral valve (MV) diagnosis so common due to the changing lifestyle in day to day life. The increased number of MV disease necessitates the development of automated disease diagnosis model based on segmentation and classification. This paper makes use of deep learning (DL) model to develop a MV classification model to diagnose the severity level. For the accurate classification of ML, this paper applies the DL model called convolution neural network (CNN-MV) model. And, an edge detection based segmentation model is also applied which will helps to further enhance the performance of the classifier. Due to the non-availability of MV dataset, we have collected a MV dataset of our own from a total of 211 instances. A set of three validation parameters namely accuracy, sensitivity and specificity are applied to indicate the effective operation of the CNN-MV model. The obtained simulation outcome pointed out that the presented CNN-MV model functions as an appropriate tool for MV diagnosis.

Keywords* : *Mitral valve; Deep Learning; CNN; Classification; Segmentation.

I. INTRODUCTION

In every human body, heart is an important part and the heart related disease is considered as a major reason for increased death rate around the globe. In recent years, a rapid increase in the number of mitral valve (MV) interventions takes place in Germany [1]. Numerous therapies are available for MV disease and are classified into two kinds namely valve replacement and valve reconstruction. Different pathological circumstances of the heart system can be identified in various signals relevant to heart like electrocardiographs (ECGs), heart sound signal, etc. From the available heart relevant signals, the action of listening to sounds of the heart is not only a comfortable option; however; it is a non-invasive method commonly employed in basic diagnosis of MV. But, the precision level of listening the action of heart is based on the talent and experience of the doctors that can be gained from long-term experience [1]. As a result, an objective and automated computer assisted model to investigate the signals of the heart sound is highly needed. Presently, automated classification of heart sounds has the capability to screen for pathology in different clinical applications that enables to minimize the expensive and time consuming in-person investigation [2].

While investigating the sounds of heart, it is analyzed in a set of four portions namely mitral, tricuspid, pulmonary and aortic. The sound is observed in every segment and is validated together for identifying abnormalities and computes the origin of the issue. Mitral valve (MV) takes the flow of blood from the left atrium to the left ventricle. The minimization of MV opening leads to the cause of Mitral Stenosis (MS) which could lead to severe heart injury. This paper has been concentration on the development of diagnosis model for MV disease. Due to the abnormal functions present in the heart, the reflection should show in the heart sounds which come from MV which is commonly employed for the identification of abnormality. The heart sound can be observed by using stethoscope. A major issue of this method lies in the requirement of more knowledge and experience of a doctor.

In addition, the issues like un suitable ecological conditions and patient inaptness could leads to deficiency in diagnosis. Every individual reason leads to the development of support system for assisting physicians to validate heart sound. This system allows to effectively interpreting the heart sounds and leads to precise identification. The analysis of the heart sound can leads to precise identification. The process of investigating heart sound using a computer is simple and inexpensive compared to the use of a stethoscope. At the same time, the medical imaging plays a important role MV analysis. Generally, MV image classification comprises a set of three processes namely segmenting images, extracting features and classifying images. The process of precisely segmenting the MV images acts an important part succeeding feature extraction and classification. The procedure of image segmentation forms a concept of splitting an image to set of parts that encloses it. It intends to partition the needed parts of the image. On the other hand, image classification models aims to identify and then classifies the images into different categories for assisting the medical doctors to identify diseases effectively. Nygaard et al. [3] examines the intensity of MV by calculating the attributes of transvalvular pressure by examining the spectrum of cardiac systolic murmur. Hebden and Torry [4] proposed a model to differentiate the systolic murmurs of aortic stenosis as well as MV regurgitation by computing the frequency contents. Bruscoand Nazeran [5] defined a smart PDA based applicable digital phonocardiograph which cannot record the heart beats; but, different signal processing as well as statistical models are applied to classify the signals as 4 sets like S1, systole, S2 and diastole. Then, it stimulates the Multilayer Perceptron (MLP) to divide the input by using five divisions such as normal, aortic regurgitation, aortic stenosis, mitral regurgitation and mitral stenosis.

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Herold et al. [6] deployed a methodology to investigate the heart beat from aortic valve stenosis by utilizing the wavelet filtering and envelope processing. It process the communication based on these envelopes. Also, Voss et al. [7] applied with a scheme to find aortic valve stenosis at primary stage. It applies wavelet as well as Fourier transform (FT) to extract suitable attributes of the heart beat signals, and linear discriminant function is employed to predict the aortic valve stenosis from these features.

Higuchi et al. [8] established a three-layer Artificial Neural Network (ANN) of phonocardiogram that records the state of heart murmurs. Ahlstrom et al. [9] modeled a technique to classify the systolic heart murmur. It encloses distinct operations as well as Neural Network (NN) is used to divide the murmurs. A Decision Tree (DT) classification model has been applied to discover different aortic stenosis from mitral regurgitation applying heart sound Pavlopoulos et al. [10]. Chauhan et al. [11] utilized an automated classifier to analyze heart sound under the application of probabilistic technology named Mel-frequency cepstral coefficients (MFCC) and Hidden Markov Models (HMM). Additionally, there are some methods used to detect the heart beat signal automatically, they are Doppler Heart Sound (DHS), Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) [12-15]. Turcoglu et al. [12] introduced a novel classifier that helps to obtain features from DHS by using wavelet and short time FTs. Then, back-propagation NN has been employed for classifying images. Uguz et al. [13] and Comak et al. [14] devised a HMM and Support Vector Machines (SVM) to develop an automated identifying device.

Although different works has been done to diagnose the MV problem, there is still a need to properly accomplish in various ways.This paper makes use of deep learning (DL) model to develop a MV classification model to diagnose the severity level. For the accurate classification of ML, this paper applies the DL model called convolution neural network (CNN-MV) method. An edge detection oriented segmentation technique is also applied which will helps to further enhance the performance of the classifier. Due to the non-availability of MV dataset, we have collected a MV dataset of our own from a total of 211 instances. A set of three validation attributes like accuracy, sensitivity and specificity are applied to indicate the effective operation of the CNN-MV model. The obtained simulation outcome pointed out that the projected CNN-MV model functions as a proper tool for MV diagnosis.

The formulation of the paper is given as follows. Section 2 defines the presented CNN-MV model briefly. Section 3 investigates the obtained simulation outcomes and Section 4 derives the conclusion of the study.

II. THE CNN-MV MODEL

The performing strategy of CNN-MV method is depicted in Fig. 1. It is comprised with collection of sub processes such as preprocessing, segmentation and classification. Herr, pre-processing stage remove the irregular parts of image like noise, blurring etc.

A. Image Segmentation

Edge detection is an essential method for segmenting images. It transforms the original images into edge images and obtains merits with the application of oriented gray scale values of an image. The edge detection considers the location of significant differences of a gray level image and the recognition of the physical and geometrical features of the objects in the scene. It basically performs detection and outlining of an object and provides a boundary between objects and background in an image. It detects the considerable discontinuity present in the image. The edges are local variations in the intensity level of the images. Generally, edges displays on the boundaries of 2 regions. The main parameter of this model is feature extraction of an image. These obtained features are applied for detecting the edges present in used clinical MR images.

B. CNN for image classification

CNN is a feed-forward NN where the data flow occurs in a single direction starting from input to output. Likewise, ANN and CNN is derived from visual cortex of brain which has alternate layer of simpler and complex class. CNN model includes a collection of conv. and pooling layers that is gathered into modules. Multiple Fully Connected (FC) layers, as a general feed-forward NN, apply these modules. Fig. 2 shows the standard CNN model for the process of image classification. Here, input image has been offered directly to the network and follows different levels of convolution and pooling. Then, a presentation of this function is induced for several FC layers. Finally, the last FC layer offered a class label to input image.

C. Convolutional Layers

This layer acts as a feature extractor, and hence it learns the representation of features of the input images. Neurons present in conv. layers are organized as feature maps. Every individual neuron of a feature map attains a receptive field that is linked to nearby neurons of proceeding layer through a collection of training weights, rarely called as filter bank [15]. The input and the learned weights perform convolution process for computing a fresh feature map, and the convoluted output is provided to a non-linear activation function. Every neuron in a feature map holds a limited weight. But, diverse feature maps in the identical conv. layer holds diverse weights, hence diverse features undergo extraction at every location [15]. Furthermore, the kth output feature map Y_k is determined as

$$Y_k = f(W_k * x) \tag{1}$$

where x indicates the input image and W_k is the conv. filter concerned with the kth feature map, * indicates the 2D conv. operator that is utilized to determine the inner applicant of a filter model at every position of an input image; and $f(\cdot)$ indicates the non-linear activation function which allows to extract the nonlinear features. At present, rectified linear unit (ReLU) become popular.

D. Pooling Layers

This layer reduces the spatial resolution of feature maps which results in spatial invariance to provide distortion as well as translation. At the beginning, it is common way to utilize average pooling aggregation layers for propagating every input layer of a smaller neighborhood of an image. Recently, max pooling aggregation layers disseminates the high rates in a receptive field to consecutive layer. Officially, max pooling chooses greater component in every receptive field so that

$$y_{kij} = \max_{(p,q) \in \Re_{i,j}} x_{kpq} \quad (2)$$

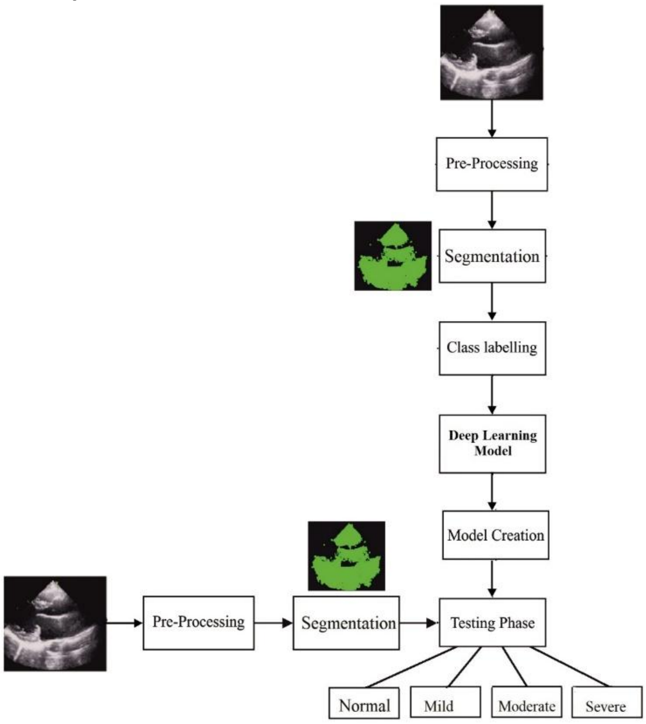


Fig. 1. Overall Process of CNN-MV model

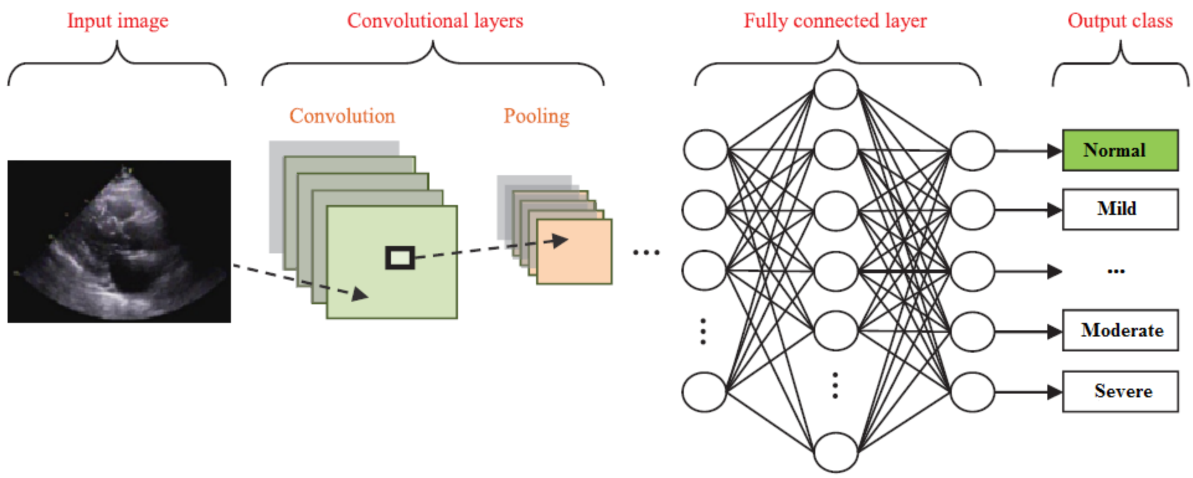


Fig. 2. CNN model for MV classification

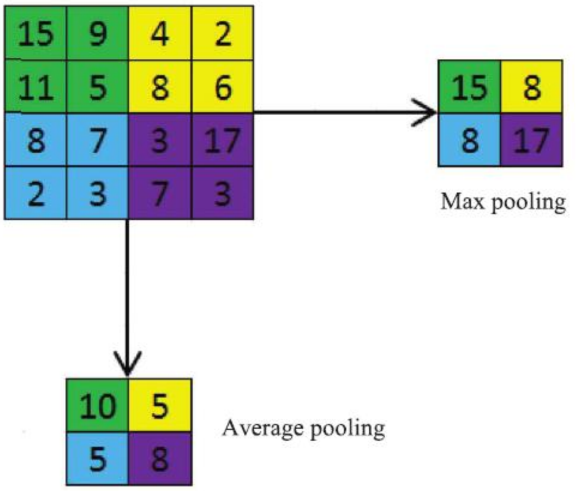
where the simulation outcome of pooling task, compared with kth feature map, Y_{kij}, x_{kpq} denotes the component at position (p, q) present in the pooling region $\Re_{ij}$, that includes a receptive field of position (i, j). Fig. 3 shows the variation of max pooling as well as average pooling layers. Let an input image of size 4 × 4, 2 × 2 filter and 2 strides are applied, max pooling provides the higher rate of every 2 × 2 region, whereas average pooling layer provide the average rounded integer value of every sub-sampled area.

E. Fully Connected Layers

Diverse conv. as well as pooling layers are generally piled on top of every other for extracting more abstract feature representation moves in the network. The FC layers understand feature representations and carry out the process of maximum-level reasoning. The softmax operator is applied to for classifying images on the top of deep CNN.

F. Training

CNN utilizes the learning method for adjusting the free variables for attaining the required network output. A widely employed for this intention is back propagation. It determines the gradient of an objective function for determining the way of adjusting the network variables for minimizing the errors which influences the overall results.



III. PERFORMANCE ANALYSIS

A. Dataset details

For the validaion of efficient performance of the introduced CNN-MV model, a dataset is collected by our own. The dataset is gathered from a total of 211 instances under four levels namley normal, mild, moderate and severe. In the total number of 211 instances, a total of 53 instances comes under the 'normal level' with the label '0'. Similarly, a total of 82 instances comes under the 'mild level' with the label '1'. Also, a total of 37 instances comes under the 'moderate level' with the label '2'. Moreover, a total of 39 instances comes under the 'severe level' with the label '0'. This information is given in Table 1 and Fig. 4 illustrates the sample images.

Table 1 Dataset Description

Levels of Mitral Valves	Number of Instances	Corresponding Labels
Normal	53	0
Mild	82	1
Moderate	37	2
Severe	39	3

B. Performance Measures

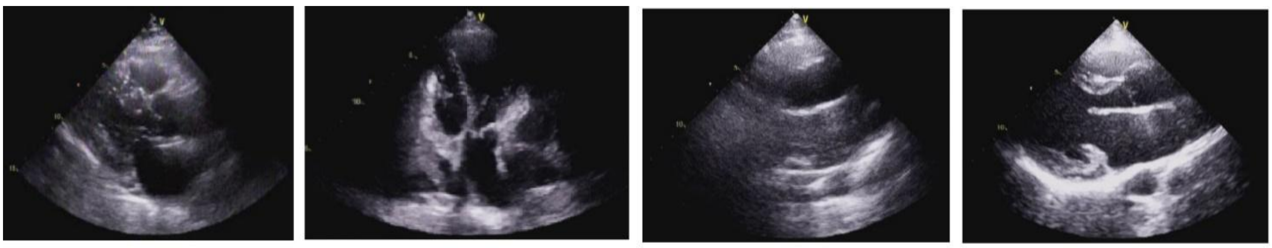
For analyzing the results of attained by the presented CNN-MV model, three evaluation parameters namely sensitivity (S_s), specificity (S_p) and accuracy $(Accu.)$ are employed and are defined below.

$$S_s = \frac{TP}{TP + FP} \tag{3}$$

$$S_p = \frac{TN}{TN + FP} \tag{4}$$

$$Accu. = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Where TP, TN, FP and FN represent true positive, true negative, false positive and false negative correspondingly.



(a) Normal (b) Mild (c) Moderate (d) Severe

Fig. 4. Sample test images

C. Results analysis

Table 2 depicts the sample output of the devised CNN-MV model with respect to different severity levels. The second column in the table depicts the actual input image. The third and fourth columns indicate the segmented and classified images respectively. From the table, it is apparent that the presented CNN-MV model precisely classifies the classified images under each category.

Table 3 provides the derived confusion matrix of the employed CNN-MV model. From the table, it is comprehensible that the CNN-MV model suitably classifies 51 images as normal out of actual 53 normal instances. At the same time, the CNN-MV model suitably classifies all the 61 images as mild out of actual 82 mild instances. In the same way, the CNN-MV model suitably classifies 10 images as moderate out of actual 39 moderate instances.

Table 2 Results of Mitral Valve Problem

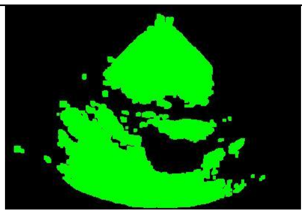
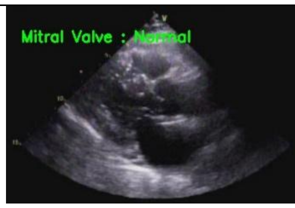
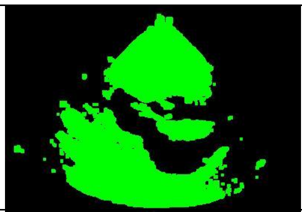
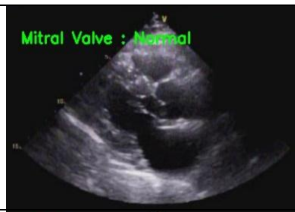
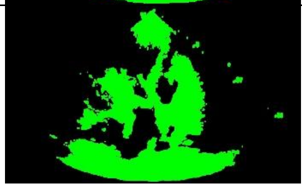
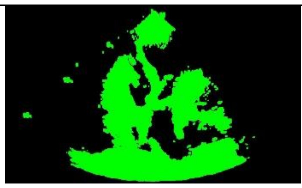
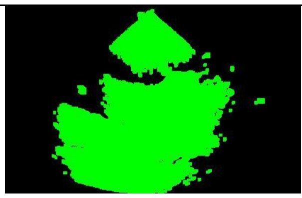
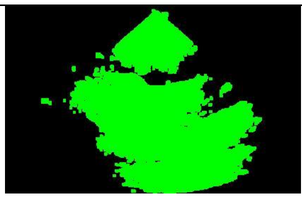
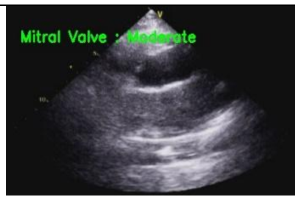
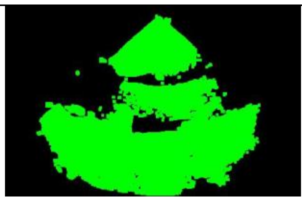
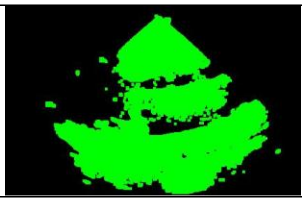
Different Levels	Original Image	Segmented Image	Classified Image
Normal			
			
Mild			
			
Moderate			
			
Severe			
			

Table 3 Confusion Matrix of Levels in Mitral Valves

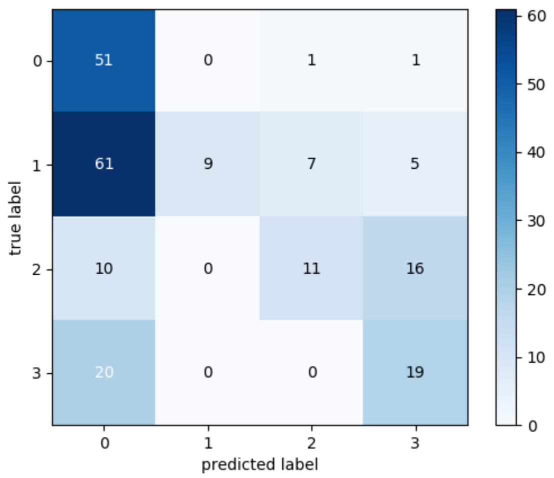


Table 4 Confusion Matrix

Input Label	Different Level of Mitral Valves				Total No. of Images
	Normal	Mild	Moderate	Severe	
Normal	51	0	1	1	53
Mild	61	9	7	5	82
Moderate	10	0	11	16	37
Severe	20	0	0	19	39
Total No. of Images	142	9	19	41	211

Additionally, the CNN-MV model properly classifies all the 20 images as severe out of actual 42 severe instances. The confusion matrix shown in Table 3 is transformed to an actual table format as shown in Table 4.

Table 5 Performance Measures of Test Images with Different Levels

Measures	Accuracy	Sensitivity	Specificity
Normal	55.90	96.20	42.40
Mild	65.40	11.00	100
Moderate	83.90	29.70	95.40
Severe	80.10	48.70	87.20

Table 5 offers the obtained outcome of the employed CNN-MV model under dissimilar levels of severity interms of three measures. The table values indicated that better performance is attained with the higher accuracy of 55.90, sensitivity of 96.20 and specificity of 42.40 is achieved under the severity level of normal. It is also exhibited that higher accuracy, sensitivity and specificity of 65.40, 11 and 100 are attained under the severity level of mild. It is observed that maximum accuracy of 83.90, sensitivity of 29.70 and specificity of 95.40 is attained under the severity level of moderate. At the end, it is apparent that the maximum accuracy of 80.10, sensitivity of 48.70 and specificity of 87.20 is achieved under the severity level of severe.

Fig. 5 depicts the investigation of the results obtained by the applied CNN-MV model under varied severity level interms of accuracy. As the figure indicates, it is understandable that moderate level is appropriately classified on all the applied instances and achieved a maximum accuracy of 83.90.

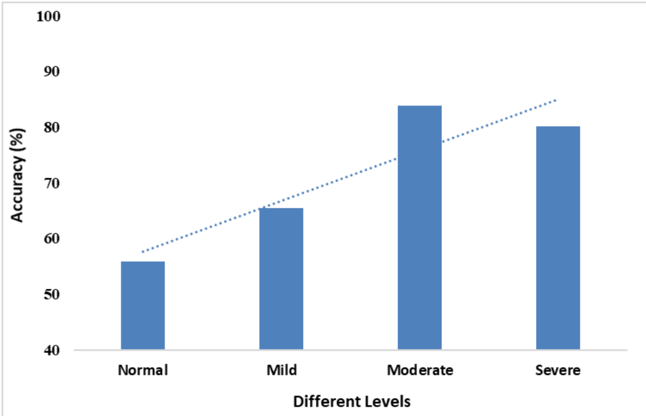


Fig. 5. Comparative analysis of accuracy under varying levels of MV severity

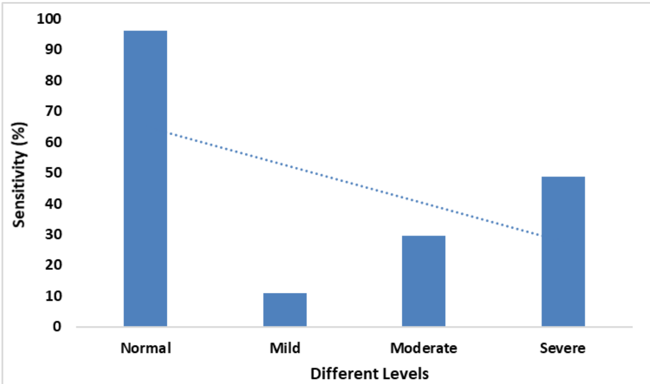


Fig. 6. Comparative analysis of sensitivity under varying levels of MV severity

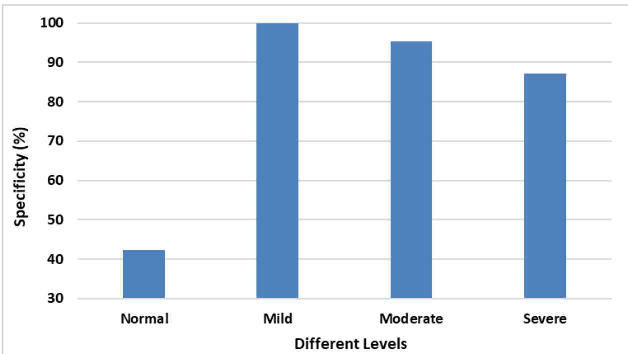


Fig. 7. Comparative analysis of specificity under varying levels of MV severity

In the same way, Fig. 6 examines the outcome obtained by the presented CNN-MV model under diverse severity level interms of sensitivity. As shown in figure, it is noticeable that normal level is suitably classified on all the applied instances and achieved a maximum sensitivity of 96.20.

Likewise, Fig. 7 compares the results obtained by the presented CNN-MV model under diverse severity level interms of specificity. As shown in figure, it is obvious that mild level is correctly classified on all the applied instances and achieved a maximum specificity of 100.

Table 6 tabulated the extensive comparison results of the applied CNN-MV model against two existing models namely PCA-DHMM [13] and DHMM [14]. Fig. 8 portrayed the comparison of the results obtained by the presented and existing methods. From this, it is apparent that maximum average accuracy of 71.325 is obtained by the CNN-MV method where the DHMM demonstrated poor results with a minimum average accuracy of 68.35. At the same time, PCA-DHMM model shows slightly better performance over DHMM with the average accuracy value of 70.67. Similar to accuracy values, the proposed CNN-MV technique exhibits qualified outcome with higher sensitivity of 46.4. Finally, the CNN-MV model shows its superiority against compared methods interms of specificity too. A maximum specificity value of 81.25 is acquired by the presented CNN-MV method whereas the DHMM and PCA-DHMM models exhibited sensitivity values of 69.08 and 72.43 respectively.

Table 6 Performance Measures of Test Images with Various Models

Methods	Accuracy	Sensitivity	Specificity
Deep Learning	71.32	46.40	81.25
PCA-DHMM	70.67	72.92	72.43
DHMM	68.35	69.28	69.08

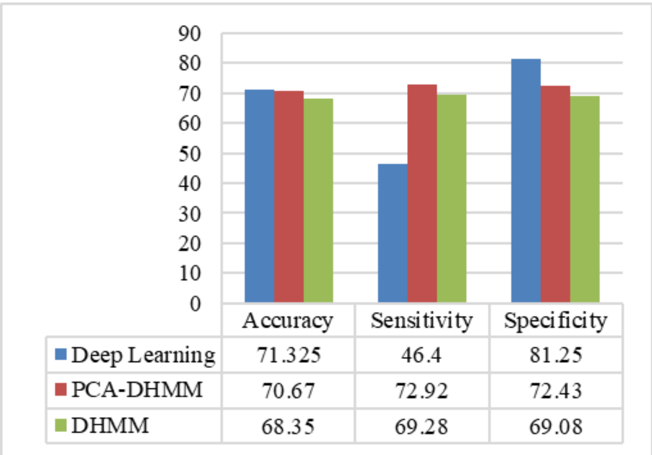


Fig. 8. Comparative classification results of diverse methods under varying levels

The detailed simulation outcome pointed out clearly that the devised CNN-MV model exhibited excellent results on every test image applied under varying levels of MV severity over the methods with respect to all the applied evaluation parameters.

IV. CONCLUSION

Presently, different image processing methodologies such as boundary detection, image classification, image segmentation, feature extraction, etc are applied to recognize the normal or abnormal functioning of heart valve. This study has concentrated on two main image processing techniques for medical diagnosis namely image segmentation and classification. Even though different works has been done to diagnose the MV problem, there is still a need to properly accomplish in various ways. This paper has developed a CNN-MV model to diagnose the severity level. And, an edge detection based segmentation model is also applied which will helps to further enhance the performance of the classifier. The obtained simulation outcome pointed out that the projected CNN-MV framework depicts a optimal final outcome with good accuracy of 71.32 and labeled as a bets tool diagnosing MV disease.

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